TabAccess, a Wireless Controller for Tablet Accessibility for Individuals with Limited Upper-Body Mobility

Hae Won Park and Ayanna M. Howard

***Abstract*— Over 3 million individuals in the US have a disability in their hands and/or forearms and thus have difficulties in effecting pinch and swipe gestures needed for tablet interaction. In this paper, a forearm mountable mobile interface, TabAccess (controller for Tablet Accessibility) is introduced. The objective is to provide an input interface for individuals with limited manipulation skills an alternative way to interact with touchscreen tablet applications. We believe that by combining TabAccess with mobile computers, effective education and entertainment opportunities could be delivered to persons lacking fine motor skills. For translation of gross motor gestures into touchscreen-based gestures, a methodology was developed to convert raw sensor data retrieved from the sensors into press and swipe gestures. The proposed device recognizes different gestures generated by a combination of sensors with hidden Markov models. This paper presents the design specifications of TabAccess, and discusses the training and testing results with three diverse applications - a music player, a robot controller, and a communication app.**

(a) Proloquo2go

(b) Popchilla

(c) Accessible Messaging

Fig. 1. Tablet computer and assistive apps for individuals with disabilities.

I. INTRODUCTION

With the current advancements in computing technology, there has been corresponding advances in technologies, such as tablet computers, that are capable of engaging individuals with disabilities or developmental delays. Numerous articles report how tablet computers are used to help children with disabilities and learning issues by actively engaging them with the device's attractive easy-to-use interface and design [1, 2]. Tablet computers are equipped with touchscreen, Wi-Fi, Bluetooth, camera, accelerometer, and GPS, which increase accessibility of these devices. Applications such as Proloquo2go [3] offer assistance to people with speech difficulties by making a sound of a word when a corresponding image is pressed or by creating a sentence when multiple images are sequenced. Popchilla [4] combines an interactive drawing application with a robot that gives feedback and responds to the user's input. Accessible Messaging [5] provides assistive text typing by highlighting every keyboard element at a time (Fig. 1).

However, these touch-based tools are developed with one basic assumption in mind: the user is capable of 'touching' a specific small region with appropriate intensity and timing. This generally does not apply to individuals who have limited motor control. Accessibility focuses on the degree to which people with disabilities can interact with the world around them. Unfortunately, most embedded applications (apps) for smartphones and tablets are not designed with accessibility in mind, especially for those with limited fine-motor control. Such individuals have difficulty in providing the common pinch and swipe gestures required for tablet control. The proposed device for tablet accessibility, TabAccess, is designed to provide an alternative input interface for increasing access to tablet-based applications. This device, coupled with a supporting tablet app software library, enables the delivery of effective education and entertainment opportunities for individuals lacking fine motor skills.

In this paper, we specifically discuss the technical design of the device and the algorithm for training and calibrating the device commands for individual customization. The mathematical modeling using hidden Markov models (HMM) will be discussed, and the results of calibration will be presented along with the applications used for testing.

II. TARGET DEMOGRAPHIC

Due to the pervasiveness of tablet devices and their ease-of-use, the emergence of tablet-based applications (apps) is fast growing. The resulting dilemma though is that with the introduction of the tablet device itself, there is an entire population of individuals with disabilities that become excluded. Unfortunately, these touch-based tools are

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Hae Won Park and Ayanna Howard are with the School of Electrical and Computer Engineering at Georgia Institute of Technology, Atlanta, GA, USA. Corresponding author's e-mail: haewon.park@gatech.edu

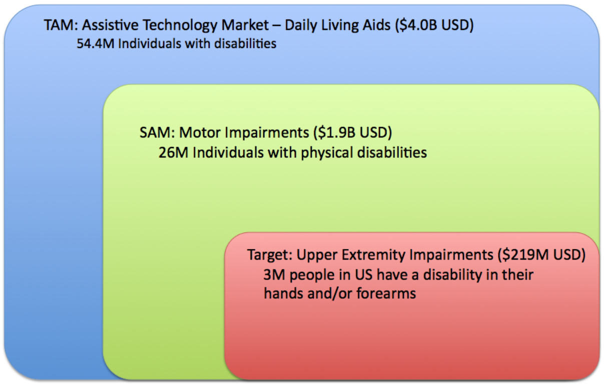


Fig. 2. Target demographic and market size.

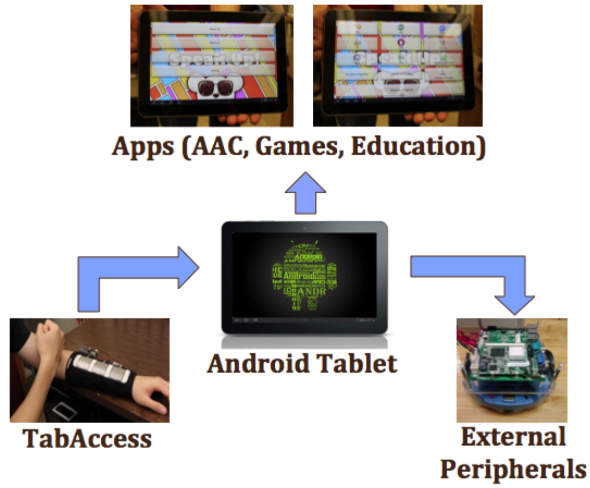


Fig. 3. System diagram illustrating TabAccess and its applications.

developed assuming an individual is capable of ‘touching’ a specific small region with appropriate intensity and timing (i.e. effecting press and swipe gestures). This assumption does not generally hold true when considering individuals who possess limited upper-body motor control, such as observed in adults and children living with cerebral palsy or recovering from traumatic brain injury. The fact that over 200,000 children with disabilities being served in the public school system have a physical disability [6], and that over 3 million individuals in the US have disabilities in their hands and/or forearms validate that there is a large demographic of individuals that are being overlooked by the introduction of the tablet device into mainstream society [7] (Fig. 2).

III. APPROACH

In this section, a preliminary design of the TabAccess interface device and its application are presented. The TabAccess system modules are designed to communicate through Bluetooth. Fig. 3 depicts the interaction between the modules. The system incorporates a forearm-mounted input device, apps implemented on a tablet, and a robot representing external peripherals that could be controlled by the tablet.

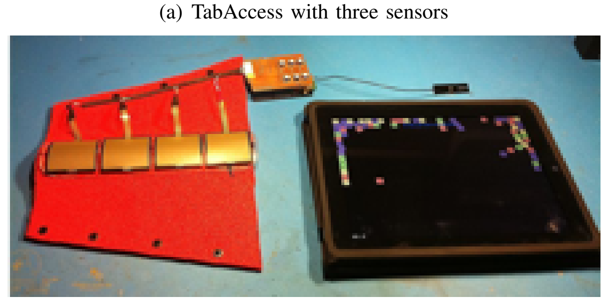
Since the range of motion and sensitivity of an individual’s motor movement can have large variations, pattern recognition techniques using Hidden Markov Models (HMMs) has been applied to customize interaction with the device. The three-step customization process employed consists of vector quantization, HMM training, and maximum likelihood evaluation.

A. Design

The motivation for our design began by examining the results of a study which reviewed a number of different joysticks and switches for use by children with motor impairments [8]. The basic purpose of the study was to develop electronic devices to extend the capability of children with Cerebral Palsy. Motivated by this study, three aspects were considered when designing TabAccess.

First, the device must provide mobility and be operable by individuals without dexterous motor control. This problem was addressed by adapting the slammer switch (a single-switch input device), which was the easiest to use, into an n-selection wireless input device, that could provide the most versatility for access to a touchscreen device. The current prototype of the forearm mountable device version is designed to slide onto the arm like a sleeve and has three to four large interaction areas. The device sensors are

(a) TabAccess with three sensors



(b) TabAccess with four sensors

Fig. 4. TabAccess is a wireless controller for individuals with motor impairments designed to provide access to the world through tablet interaction.

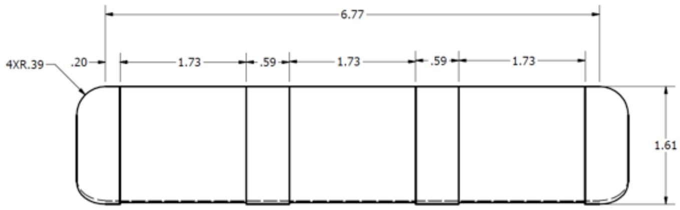


Fig. 5. Sensor mount and associated dimensions.

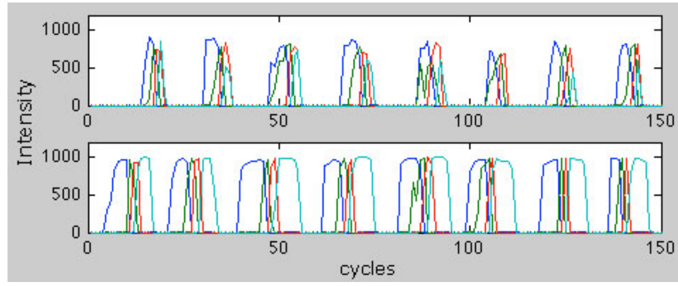
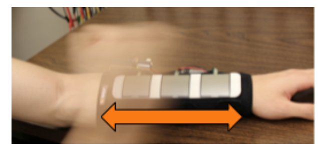


Fig. 6. Two subjects performing *Swiping*. Notice not only the intensity but also the duration on each sensor value differs.

(a) Button press



(b) Swipe

Fig. 7. Two types of gestures. The readings from the sensors are transmitted wirelessly to the tablet platform.

placed on an adjustable brace to allow custom fit for the user's forearm as shown in Fig. 4. Force sensitive resistors (FSRs) were selected in order to cope with different user capabilities. The pressure intensity to activate each sensor could be adjusted using a threshold for each individual, and compared to conductive sensors, FSRs could be operated using non-conductive surfaces, such as gloves, clothes, or prosthetic devices. Each FSR is wired to a voltage-divider circuit, which are inputs to a microcontroller. The current design also incorporates a custom sensor mount with a curved base and raised edges that are flush with the sensors allowing for a smooth interaction with the sensors (Fig. 5). Furthermore, the sleeve also contains a microcontroller that interprets the inputs received from the sensors and classifies them into a gesture.

Second, the device should be able to output multiple commands with an option to calibrate and customize the commands to match individual's range of motion. While observing subjects interacting with the device, we found that each individual varied in how they use the device. Some applied force with the large side of their fist, some with their narrower side, some with their hand open, and others using just their index finger. This made us consider implementing training and calibration as an essential part of the device which individuals with upper-limb mobility deficiencies can access given their effective range of motion [9]. Fig. 6 shows two different subjects performing a *Swipe* (swiping across four sensors). For translation of gross motor gestures into touchscreen-based gestures, we have developed a methodology to convert raw sensor data retrieved from the sensors into press and swipe gestures (Fig. 7). This provides the ability to generate a number of unique gesture commands using the wireless device (i.e. by pressing one of the three resistive force sensors or performing a forward swipe or reverse swipe, which occurs when the user slides their hand, fist, or arm across multiple sensors in either direction). Once generated, the readings from the sensors are transmitted wirelessly to the tablet platform via a Bluetooth connection and decoded by our app interface protocol, which runs in the background and provides input interrupts to the currently active app.

Lastly, the device should be an affordable off-the-shelf product that is truly accessible to any person in need. The total cost of building the discussed prototype was $148 US dollars.

B. Gesture Recognition using HMMs

In order to recognize meaningful signals from the sensors, we trained six different gestures with hidden Markov models (HMMs). HMM is a doubly stochastic process, an extension of discrete Markov chains, which cannot be directly observed. Gesture recognition using HMMs has been developed extensively during the past decade. Starner et al. [10] describe an extensible system which uses one color camera to track hands in real time and interprets American sign language (ASL). They use HMMs to recognize a full sentence and demonstrate the feasibility of recognizing a series of complicated gestures. Play behavior recognition for a robot playmate [11] also uses HMMs to recognize and sequence basic play primitives that helps understand the way a child plays. Recognizing gestures using sensor data from an input device, similar to the intent of this paper, was presented in [12]. In this work, the authors verify how HMM could be used to recognize predefined gestures from a sequence of accelerometer sensor data.

A discrete HMM is represented by three matrices, $\lambda = (A, B, \pi)$. The matrix $A = \{a_{ij}\}$ represents the state transition probability from state i to j. $B = \{b_{jk}\}$ specifies the probability of generating observational symbol k from state j, and π indicates the initial state probability distribution. There are three basic problems that need to be addressed for modeling data patterns using HMM [13]: evaluation, decoding, and training (optimizing). The solutions to these problems are found using variations of the Forward-Backward, Viterbi, and the Baum-Welch algorithms.

In this research, six HMMs were trained and tested: *press and release* of the four buttons, *forward-swiping* in the direction from button 1 to button 4, and *reverse-swiping* in the direction from button 4 to button 1. These combinations were defined for basic evaluation purpose, but the biggest

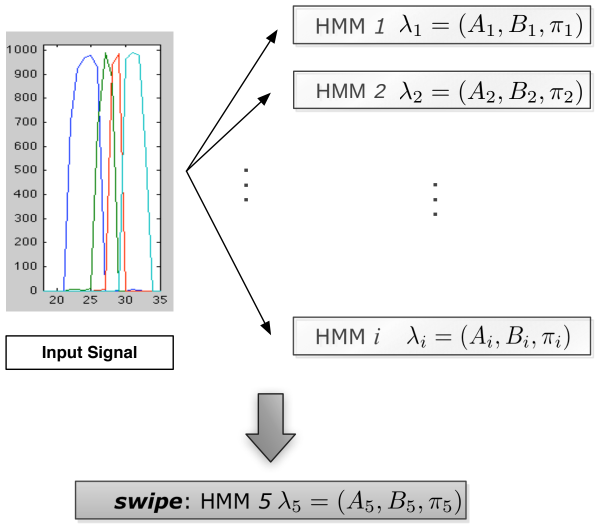


Fig. 8. Input signal sequence is evaluated and the hidden Markov model with maximum likelihood is selected.

advantage of using HMMs is that it can be customized to each individual's needs and ability. For example, if a subject experiences difficulty swiping through all the four sensors, the device can be trained to recognize swiping as a swipe through the last two sensors.

Before applying raw sensor data to the HMMs, an array of four sensor values are quantized into discrete symbols. The four sensors are classified as either *on* or *off* with a low threshold. The combination of four sensor states generate $2^4 = 16$ codes. After a sequence of sensor value vectors $\vec{S} = \vec{S}_1\vec{S}_2\vec{S}_3...$ are converted into discrete observation symbols $\vec{O} = \vec{O}_1\vec{O}_2\vec{O}_3...$, the sequence data is used either to train the HMM $\lambda_i = (A_i, B_i, \pi_i)$ or to recognize which HMM it belongs to by computing the maximum likelihood $arg\max_{\lambda_i}[P(\vec{O}|\lambda_i)]$, where $i = 1...6$. Fig. 8 shows a sample input sequence being evaluated.

IV. EXPERIMENTAL RESULTS

A. Experimental Setup

To evaluate the training and recognition performance of the command inputs, six subjects were recruited to interact with TabAccess. First, sensor data was collected for training and testing purposes where the subjects executed each command using their most comfortable configuration. Next, the subjects were invited to explore our two types of software: a computer application and a tablet app. In the results, the accuracy of the hidden Markov model (HMM) system is measured, and the performance of the overall interaction with TabAccess is evaluated.

B. Training

In this work, we trained HMMs to recognize six gestures with a four-sensor TabAccess. The purpose of training HMMs for every user is to calibrate and customize the device to accommodate each individual's range of motion and adjust the intensity required for operating the device. We collected 250 samples of data for each gesture per subject. The average sampling rate was 19.62 Hz, and the subjects were asked to repeat the same gesture during the data collection. Fig. 10 shows an example of data collection for 150 cycles. Six subjects participated in the study, and the total training time for each subject ranged from 76 to 97 seconds.

C. Testing and Evaluation

Following the training session, testing data was collected in the same manner as the training data. Fig. 11 shows the

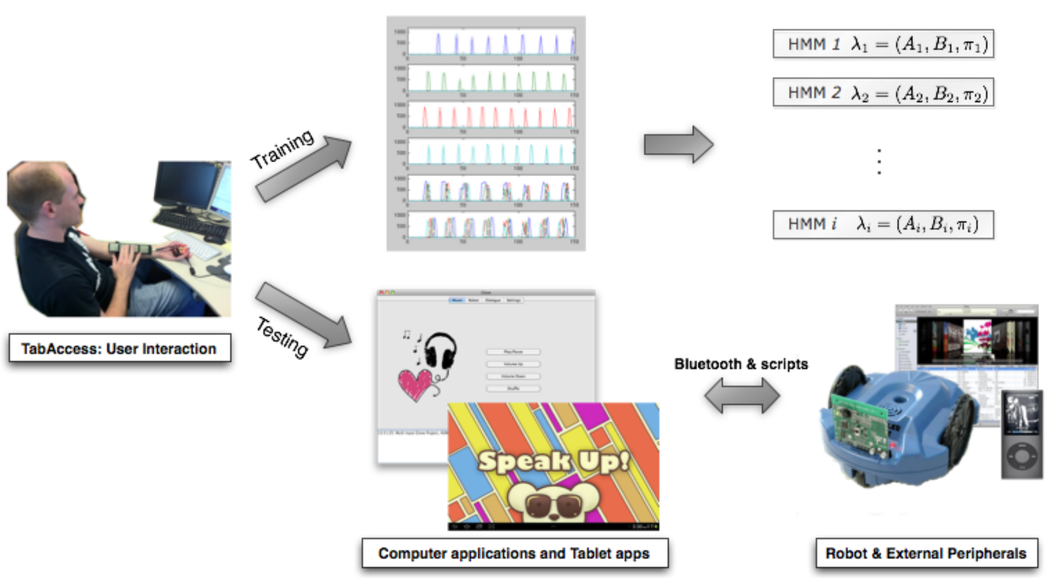


Fig. 9. Experimental setting: The user first trains TabAccess by providing sequences of each command to the system. The user can use the calibrated device to interact with computer applications and tablet apps.

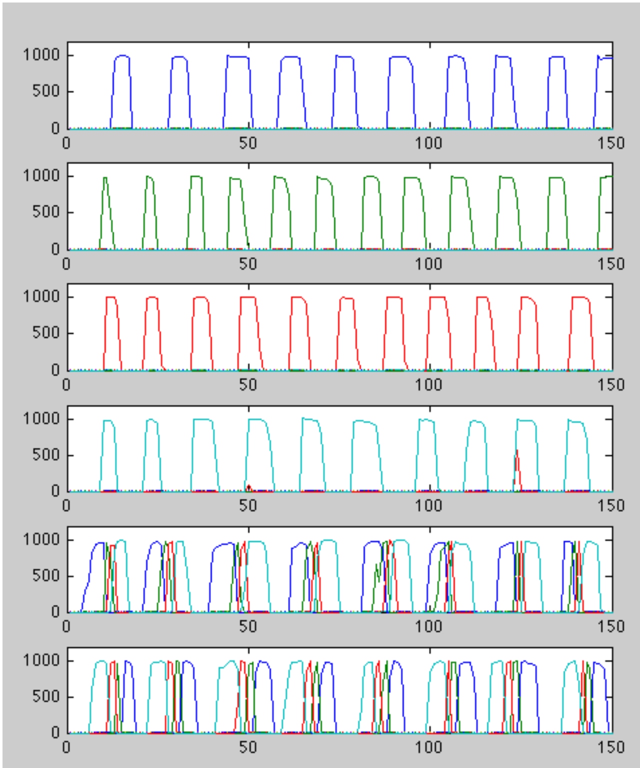


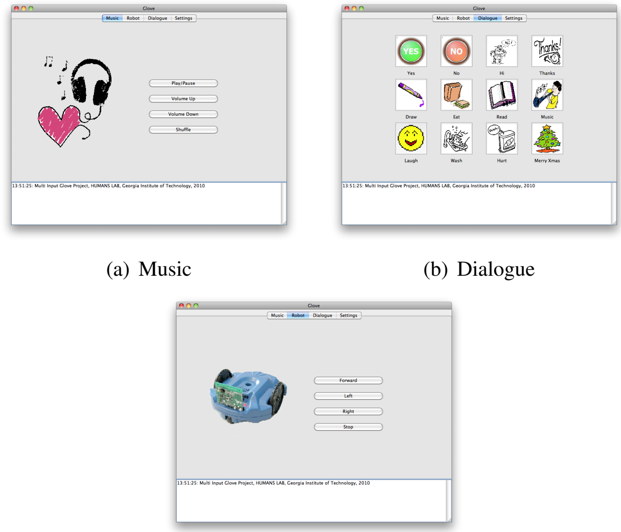
Fig. 10. Data collection (150 cycles) - Top to bottom: Button 1, Button 2, Button 3, Button 4, Forward-swiping, and Reverse-swiping.

recognition rate for each command and a confusion matrix. The overall average recognition rate was 96.35%.

Afterwards, the subjects freely navigated through the computer application and the tablet app including their external peripherals, such as a music player and a robot. The computer application implemented on Mac Mini plays music, launches communication application, and drives a robot via Bluetooth by sending a script (Fig. 12). *Forward-* and *reverse-swiping* navigates through the applications back and forth. The four button presses are configured to execute dif-

Predicted	Observed: Button1	Button2	Button3	Button4	Swipe	Reverse-Swipe	Recognition Rate (%)
Button1	62				1		98.41%
Button2		65				1	98.48%
Button3			68			2	97.14%
Button4				67			100.00%
Swipe					53	2	96.36%
Reverse-Swipe	4			1	3	55	87.30%
Average							96.35%

Fig. 11. Confusion Matrix: predicted versus observed number of test sequences are shown. Six subjects participated in the study resulting in an average recognition rate of 96.35%.



(a) Music (b) Dialogue

(c) Robot

Fig. 12. Computer application: *Swiping* and *reverse-swiping* navigates through the applications, and *pressing* buttons triggers different events on each application.

ferent functions on each application. For example, if the user navigates through the menus and chooses to listen to music, the four button presses serve as play/pause, volume up and down, and shuffle playlist. The tablet app called SpeakUp (Fig. 13) uses the image and text-to-speech models provided by the TabAccess application. The application also utilizes the TableLayout to define the view. Within SpeakUp, there are multiple buttons corresponding to different phrases. The user navigates the application with TabAccess and selects a button similar to the functional input of a tablet. SpeakUp is an example of a functional software-based applications. Game and robot programming apps are also created using the same layout. The gaming app is aimed at teaching new users how to operate TabAccess by means of an image-matching memory game. The robot-programming app allows the user to program the robot using directional commands as well as macro recording that sends sequenced commands to the robot.

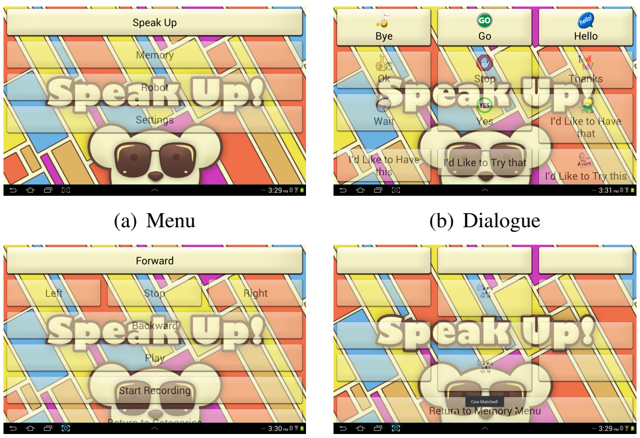
Aside from the accuracy of the sensor pattern recognition, sensor responsiveness, sensor reliability, sensor response time, command pattern recognition time, and device connection reliability were measured (Table I). The result demonstrates that the gestures generated by different combinations of the sensors can be easily trained and recognized in real time while providing stable connection to the tablet.

V. CONCLUSION

This paper presents the basic concept of a touchscreen tablet computer controller for individuals with limited upper-body motor skills. The purpose of TabAccess is to engage such individuals in both therapeutic and entertaining interactions with mobile computers. The main contribution of our work is in introducing a novel input device for

TABLE I
PERFORMANCE MEASURES

Metric	Description	Measurement	Result
Sensor Responsiveness	Ability to detect when human accesses device	Percent Error	2%
Sensor Reliability	Ability to detect individual sensor input with adjustable threshold	Percent Error	3%
Sensor Response Time	Time between input and sensor detection	Average Time	$<$ 1ms
Pattern Recognition Time	Ability to identify correct sensor pattern	Average Time	$<$ 1ms
Connection Reliability	Ability for the application to maintain connectivity while in use	Percentage of Reliability	99%



(a) Menu (b) Dialogue

(c) Robot Programming (d) Memory Game

Fig. 13. Tablet app (SpeakUp): *Forward-* and *reverse-swiping* navigates through the rows, and *pressing* buttons triggers columns on each row.

tablets that can be easily trained for individual users' range of motion while providing access to a range of applications. The device is designed to be calibrated for each user by using hidden Markov models as a gesture pattern-recognition algorithm. The command recognition rate was 96.35%, and the user study reveals that TabAccess is highly responsive to user inputs and provides real-time interaction while maintaining stable connection to the tablet.

VI. ACKNOWLEDGMENTS

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